REPORT DOCUMENTATION PAGE

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14. ABSTRACT
This document contains an overview of research and work performed and published at the University of Florida from October 1, 2009 to October 31, 2013 pertaining to proposal 57306CS: Multi-object Detection and Discrimination Algorithms.

Topics By Year:
1. 2009-2010

15. SUBJECT TERMS
Landmine detection, University of Florida, machine learning, image processing, multi-sensor fusion, classifier development, ground-penetrating radar (GPR), ground boundary detection

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Report Title

Final Report: Multi-object Detection and Discrimination Algorithms

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4. 2012-2013
- Optimal Fusion of Alarm Sets from Multiple Detectors Using Dynamic Programming
- Improvements on Multiple Instance Learning Hidden Markov Model for landmine detection in ground penetrating radar data

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Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received		Paper
08/22/2012	8.00	Pete Torrione, Jeremy Bolton, Paul Gader, Hichem Frigui. Random set framework for multiple instance learning, Information Sciences, (6 2011): 0. doi: 10.1016/j.ins.2010.12.020

TOTAL: 1

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

Received	Paper

TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

Number of Presentations: 0.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
08/22/2012	13.00	Brandon Smock , Joseph Wilson. RECIPROCAL POINTER CHAINS FOR IDENTIFYING LAYER BOUNDARIES INGROUND-PENETRATING RADAR DATA, IEEE IGARSS. 26-JUL-12, . : ,

TOTAL: 1

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
03/26/2015	15.00	Taylor Glenn, Brandon Smock, Joseph Wilson. Optimal fusion of alarm sets from multiple detectors using dynamic programming, IGARSS 2013 - 2013 IEEE International Geoscience and Remote Sensing Symposium. 21-JUL-13, Melbourne, Australia. : ,
08/22/2012	4.00	Xuping Zhang, Seniha Esen Yuksel, Paul Gader, Joseph N. Wilson. Simultaneous feature and HMM Model learning for landmine detection using Ground Penetrating Radar, 2010 IAPR Workshop on Pattern Recognition in Remote Sensing (PRRS 2010). 22-AUG-10, Istanbul, Turkey. : ,
08/22/2012	12.00	Brandon Smock, Joseph Wilson. Efficient multiple layer boundary detection in ground-penetrating radar data using an extended Viterbi algorithm, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVII. , Baltimore, Maryland, USA. : ,
08/22/2012	11.00	Ryan Close, Ken Watford, Taylor Glenn, Paul Gader, Joseph Wilson. Using predictive distributions to estimate uncertainty in classifying landmine targets, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVI. , Orlando, Florida, USA. : ,
08/22/2012	10.00	Joshua Wood, Joseph Wilson, Jeremy Bolton. Extracting edge histogram detector features from ground penetrating radar data without ground alignment, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVII. , Baltimore, Maryland, USA. : ,
08/22/2012	9.00	Joshua Wood, Joseph Wilson. Support vector data description for detecting the air-ground interface in ground penetrating radar signals, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVI. , Orlando, Florida, USA. : ,
08/22/2012	7.00	Joshua Wood, Jeremy Bolton, George Casella, Leslie Collins, Paul Gader, Taylor Glenn, Jeffery Ho, Wen Lee, Richard Mueller, Brandon Smock, Peter Torrione, Ken Watford, Joseph Wilson. Comparison of algorithms for finding the air-ground interface in ground penetrating radar signals, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVI. , Orlando, Florida, USA. : ,
08/22/2012	6.00	Brandon Smock, Paul Gader, Joseph Wilson. DynaMax+ ground-tracking algorithm, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVI. , Orlando, Florida, USA. : ,
08/22/2012	5.00	R. Close, J. Wilson, P. Gader. A Bayesian approach to localized multi-kernel learning using the relevance vector machine, IGARSS 2011 - 2011 IEEE International Geoscience and Remote Sensing Symposium. 24-JUL-11, Vancouver, BC, Canada. : ,
08/22/2012	2.00	Jeremy Bolton, Paul Gader. Cross Entropy Optimization of the Random Set Framework for Multiple Instance Learning, 2010 20th International Conference on Pattern Recognition (ICPR). 23-AUG-10, Istanbul, Turkey. : ,

08/22/2012	1.00	Jeremy Bolton, Paul Gader, Hichem Frigui. Multiple instance feature learning for landmine detection in ground-penetrating radar data, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XV. , Orlando, Florida, USA. : ,
08/22/2012	3.00	Taylor C. Glenn, Joseph N. Wilson, K.C. Ho. A multimodal Matching Pursuits Dissimilarity Measure applied to landmine/clutter discrimination, IGARSS 2010 - 2010 IEEE International Geoscience and Remote Sensing Symposium. 25-JUL-10, Honolulu, HI, USA. : ,
09/24/2013	14.00	Jeremy Bolton, Seniha Esen Yuksel, Paul Gader, J. Thomas Broach, Jason C. Isaacs, Leslie M. Collins. Multiple instance learning for hidden Markov models: application to landmine detection, SPIE Defense, Security, and Sensing. 02-MAY-13, Baltimore, Maryland, USA. : ,

TOTAL: **13**

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received Paper

TOTAL:

Number of Manuscripts:

Books

Received Book

TOTAL:

Received Book Chapter

TOTAL:

Patents Submitted

Patents Awarded

Awards

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Taylor Glenn	0.13	
Ryan Close	0.03	
Peter Dobbins	0.25	
Brandon Smock	0.26	
Dmitri Dranishnikov	0.01	
Sean Goldberg	0.11	
Ken Watford	0.22	
Joshua Wood	0.04	
FTE Equivalent:	**1.05**	
Total Number:	**8**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
Seniha Yuksel	0.03
Jeremy Bolton	0.14
FTE Equivalent:	**0.17**
Total Number:	**2**

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Joseph Wilson	0.23	
Paul Gader	0.11	
Jeremy Bolton	0.27	
FTE Equivalent:	**0.61**	
Total Number:	**3**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:...... 0.00

Names of Personnel receiving masters degrees

NAME	
Ken Watford	
Joshua Wood	
Total Number:	**2**

Names of personnel receiving PHDs

NAME	
Ryan Close	
Dmitri Dranishnikov	
Total Number:	**2**

Names of other research staff

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

See Report.

Technology Transfer

This document contains an overview of research and work performed and published at the University of Florida from October 1, 2009 to October 31, 2013 pertaining to proposal *57306CS: Multi-object Detection and Discrimination Algorithms.*

Overview

Topics By Year

1. 2009-2010
    - A multimodal matching pursuits dissimilarity measure applied to landmine/clutter discrimination
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2009-2010

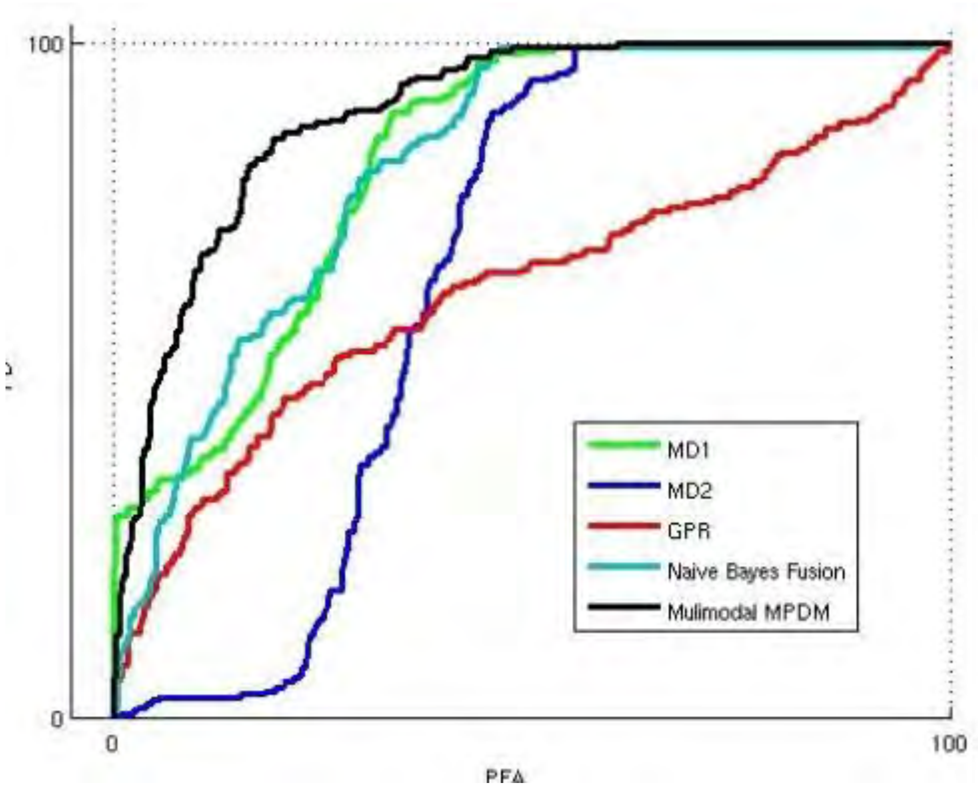
A multimodal matching pursuits dissimilarity measure applied to landmine/clutter discrimination

The focus of this research is the Matching Pursuits Dissimilarity Measure (MPDM), which is an effective way to compare signals that are sparsely approximated using a Matching Pursuits method. The CAMP algorithm uses an MPDM distance measure in Competitive Agglomeration clustering to model and classify signals. The MPDM approach can only compare signals originating from a single source. Many landmine detection systems use multiple sensors to make simultaneous measurements of the same region of interest. In this research a Multimodal MPDM that can be used with CAMP to fuse signals from multiple sensors has been developed and investigated (Glenn et al, 2010). We demonstrate the effectiveness of the Multimodal MPDM over the single sensor (hand-held device) MPDM in improving discrimination of landmines from clutter objects.

CAMP has been applied to the landmine/clutter discrimination problem in a single electromagnetic induction sensor setting in the past. The same time-domain signals employed in that work are used in
current experiments. In this work we also incorporate signal channels comprised of features captured from a frequency-swept, continuous-wave radar system. We report on evaluation of the Multimodal MPDM approach using data collected at three test sites with buried landmines and clutter objects, two temperate sites in the eastern United States and one arid site in the western United States.

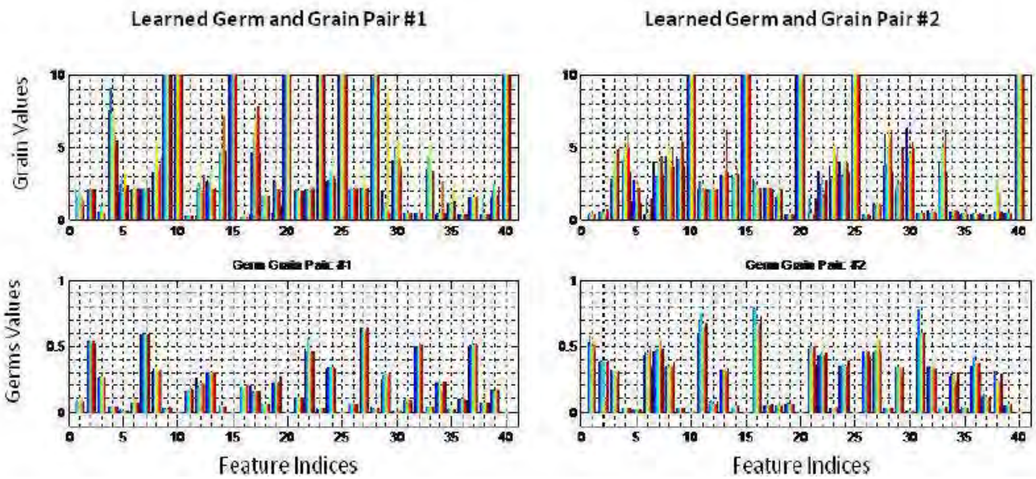
The CAMP algorithm using three different single signals, the new Multimodal MPDM using these signals, and confidence-level fusion of the single signal CAMP outputs, were tested to compare their performance. The testing was performed on a dataset consisting of signals collected from buried anti-tank and anti-personnel landmines, metallic and non-metallic emplaced clutter objects, and regions with no emplaced object. The reported results are from resubstitution testing, and therefore indicate a best-case result.

Figure below shows Receiver Operating Characteristic (ROC) plots for the CAMP algorithm using two metal detector channels and the GPR channel individually, the confidence level fusion of the outputs
using a naive Bayesian model, and CAMP using the Multimodal MPDM with all three channels. The single signals MD1, MD2, and GPR are from co-located sensors on the collection device. The GPR signal is a feature of the radar's frequency magnitude output, made from the reconstruction error of the best single sample linear predictor. The Multimodal MPDM uses the data from both the MD1, MD2, and GPR channels simultaneously.



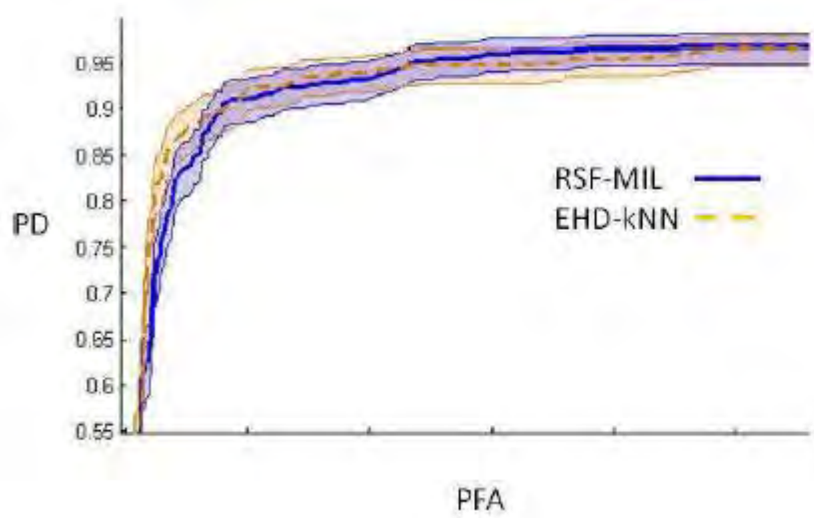
Multiple Instance Feature Learning for Landmine Detection in Ground Penetrating Radar Imagery

Our research on this topic focused on Multiple instance learning (MIL), which is a technique used for identifying a target pattern within sets of data. In MIL, a learner is presented with sets of samples; whereas in standard techniques, a learner is presented with individual samples. The MI scenario is encountered given the nature of landmine detection in GPR data, and therefore landmine detection results should benefit from the use of multiple instance techniques. Previously, a random set framework for multiple instance learning (RSF-MIL) was proposed which utilizes random sets and fuzzy measures to model the MIL problem. As noted below, an improved version C-RSF-MIL was recently developed showing a increase in learning and classification performance. This new approach is used to learn and characterize features of landmines within GPR imagery for the purposes of classification (Bolton et al, 2010). Experimental results show the benefits of using RSF-MIL for landmine detection in GPR imagery.



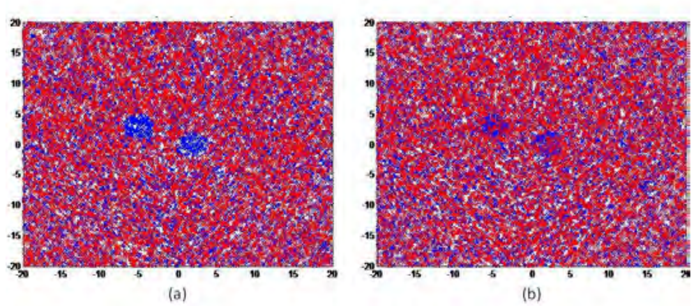
For example in each of the 10 folds during crossvalidation, features indices congruent to zero, one, two, three and four mod 5 correspond to a horizontal, vertical, rising, falling, and non-edge membership values (respectively) in the second downtrack bin (left to right). Note that in both learned germ and grain pairs, features corresponding to rising edges start at high values and slowly decrease when traversing the vector from left to right as shown above. Note that the opposite is true for the falling edge{ starting low and steadily increasing in value. Note that essentially all non-edge features are learned to be negligible. Thus each germ and grain pair has learned a hyperbolic signature. Note that the second germ and grain pair has a high horizontal feature at index 16 and lower rising and falling edge signatures. This indicates that it has learned a slightly different, elongated hyperbolic signature. The model has clearly benefited from using two germ and grain pairs to represent two distinct hyperbolic signatures. This benefit is gained from using the random set framework which permits multiple target concept models.

Classification results of C-RSF-MIL are compared to the EHD-kNN algorithm, which is currently the state- of- the-art in landmine detection using GPR imagery. Both algorithms under test were run on a collection of GPR images consisting of approximately 800 landmines and 1300 non-landmines, using 10-fold crossvalidation. The EHD classifier performs classification using kNN based approach which makes use of approximately 50- 200 prototypes (dependent on crossvalidation fold) and uses Euclidean distance as the metric. An example of a random set model consisting of two germ and grain pairs is shown in Figure below. The hyperbolic signal has been characterized.

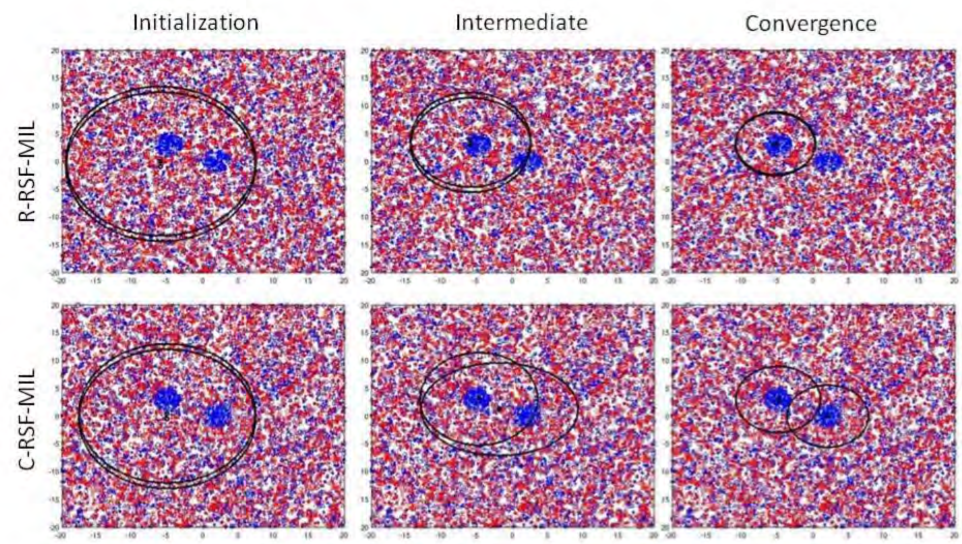


New formulations of MIL: Cross Entropy Optimization of the Random Set Framework for Multiple Instance Learning

As noted previously, Multiple instance learning (MIL) is a recently researched technique used for learning a target concept in the presence of noise. A random set framework for multiple instance learning (RSF- MIL) was proposed in previous research; however, the investigated optimization strategy did not permit the harmonious optimization of model parameters. This research focused on a cross entropy, based optimization strategy is investigated (Bolton et al, 2010). Experimental results on synthetic examples, benchmark and landmine data sets illustrate the benefits of the researched optimization strategy.



The approach was validated on synthetic data shown above, before experimentation on landmine data. R-RSF-MIL is compared to CRSF- MIL using these two synthetic datasets constructed to highlight the difference in optimization strategy. In the Disjunct dataset, a bag is constructed by drawing 15 two dimensional vectors from a uniform distribution between -20 and 20, in each dimension. Bags are labeled positive if there exists a constituent sample that lies within distance 1 of point (-5,3) or point (2,0). Bags are labeled negative, otherwise.



In the Conjunct dataset, Fig. above Optimization of R-RSF-MIL and C-RSF-MIL on the Toy data set at three stages. Germ and grain pairs are illustrated in black to indicate areas with non-negligible probability of intersection. bags are labeled positive if there exists a constituent sample that lies within distance one of point (-5,3) and there exists a sample that lies within a distance one of point and (2,0). Bags are labeled negative, otherwise. Five hundred positive and negative bags are constructed for each data set. Both RRSF- MIL and C-RSF-MIL are optimized on each data set using 2 germ and grain pairs, which are initialized randomly within [-10,10]x[-10,10]. In each data set there are two areas of diverse density: near (-5,3) and (2,0), illustrated in Figure above.

The average (over 50 experiments) Area Under the receiver operating characteristic Curve (AUC) for R- RSF-MIL and CRSF- MIL on the Conjunct data set was 0.98 and 0.98, respectively; the AUC results on the Disjunct data set were 0.99 and 0.85, respectively. In R-RSF-MIL, each of the germs were attracted to areas of diverse density nearest to its initialization point (irrespective of which area of diverse density the other germ and grain pair was attracted to). However, in C-RSFMIL, both germ and grain pairs were attracted to different areas of diverse density, irrespective of initialization. The results on the Disjunct data set illustrate this occurrence since it is necessary for both areas of diverse density to be identified by a germ and grain pair for correct classification. This was achieved using C-RSF-MIL since the germ and grain pairs are optimized in harmony. An example of this is occurrence is shown in Figure 2, where learned germ and grain models of both R-RSF-MIL and C-RSF-MIL (from one of the 50 experiments) are shown at various stages of optimization on the Disjunct toy data set.

Simultaneous Feature and HMM Model Learning for Landmine Detection using Ground Penetrating Radar

Hidden Markov Models (HMMs) have been widely used in landmine detection with Ground Penetrating Radar (GPR) data; however, to the best of our knowledge, there are no other studies that investigated the simultaneous learning of the features and the HMM parameters. In our research here, we present a novel method based on Gibbs sampling that both learns a feature extraction model as well as an HMM model (Zhang et al, 2010). The new system allows for the training of new features when the sensor systems are different. Experiments show that our algorithm is more robust to initialization and can find better solutions on GPR landmine data sets.

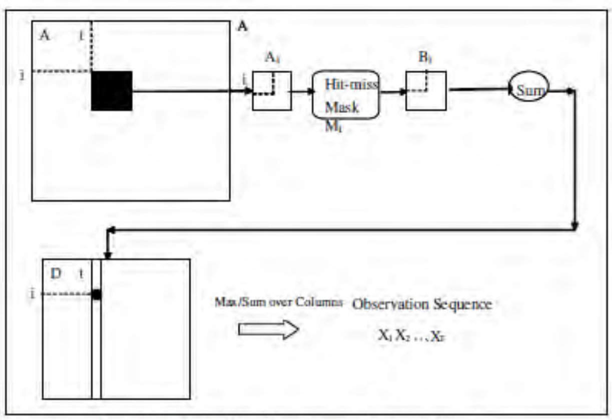


Figure 1: System for feature learning

2010-2011

A Bayesian approach to localized multi-kernel learning using the relevance vector machine

Multi-kernel learning has become a popular method to allow classification models greater flexibility in representing the relationships between data points. This approach has evolved into localized multi-kernel learning, which creates classification models that have the ability to adapt to a multi-scale feature-space. The advantages of such an approach are often hampered by additional parameters and hyper-parameters involved in creating this model, not to mention the greater likelihood of over-training. Additionally, existing methods to create a localized multi-kernel classifier rely on partitioning the feature-space, followed by applying a multi-kernel to the partitioned data points. We introduce a Bayesian approach to the localized multi-kernel machine. The new model is shown to provide greater classification abilities by learning the local scales of the feature-space without the need to partition the data. Also, the Bayesian formulation helps the model to be resistant to over-training. We demonstrate the models effectiveness on two landmine detection datasets, each from a different sensor type.

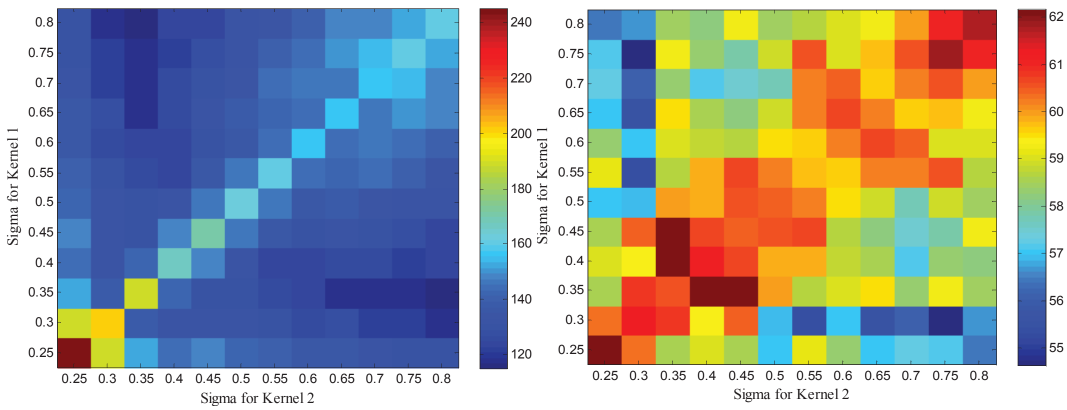


Figure 1: GPR (left) with a minimum SSE at (.35, .8), WEMI (right) with a minimum SSE at (.3, .75)

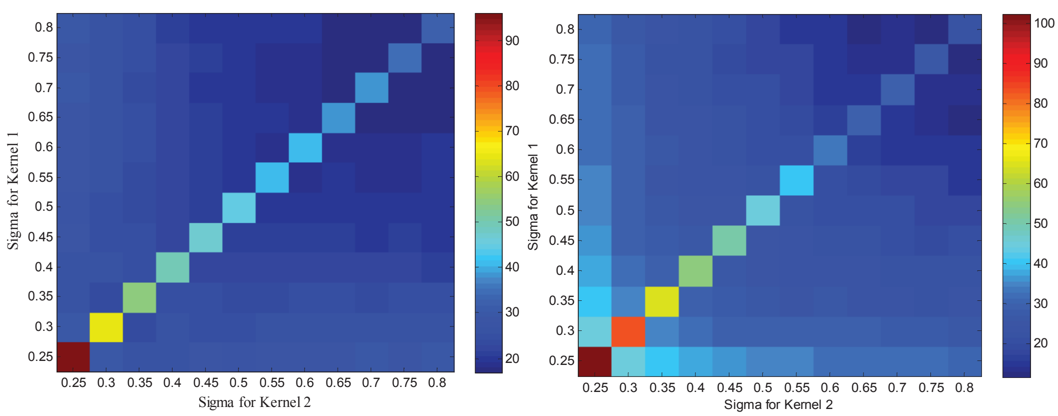
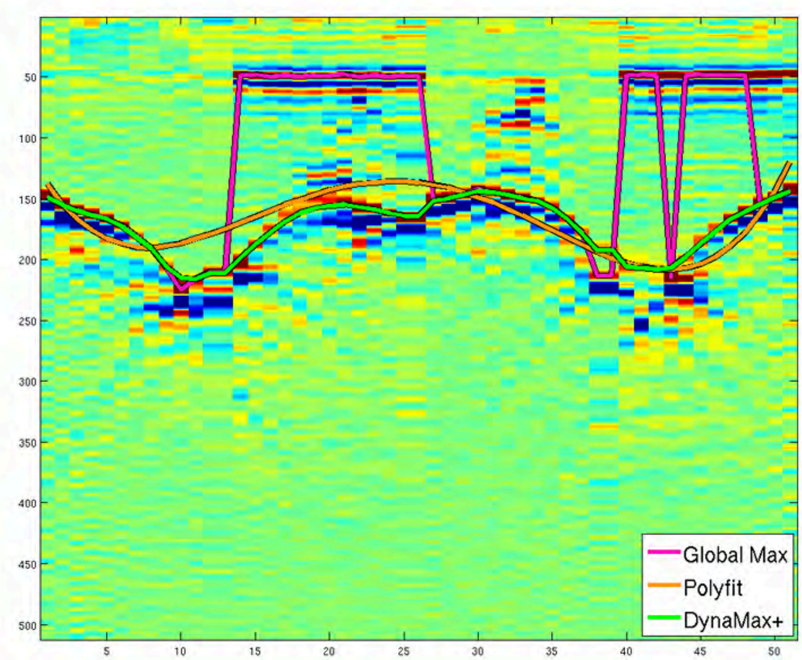
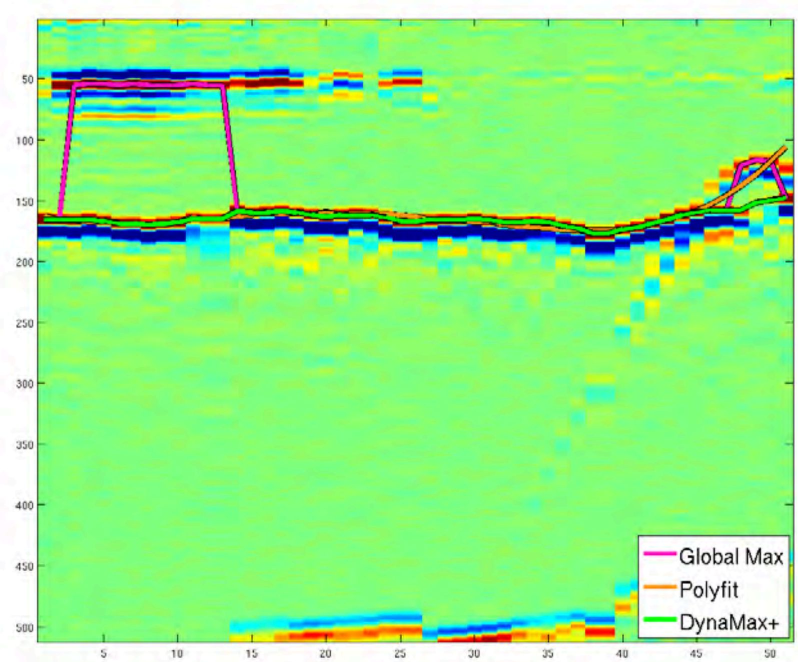


Figure 2: Mean number of relevant vectors, GPR (left) and WEMI (right)

DynaMax+ ground-tracking algorithm

In this paper, we propose a new method for performing ground-tracking using ground-penetrating radar (GPR). Ground-tracking involves identifying the air-ground interface, which is usually the dominant feature in a radar image but frequently is obscured or mimicked by other nearby elements. It is an important problem in landmine detection using vehicle-mounted systems because antenna motion, caused by bumpy ground, can introduce distortions in downtrack radar images, which ground-tracking makes it possible to correct. Because landmine detection is performed in real-time, any algorithm for ground-tracking must be able to run quickly, prior to other, more computationally expensive algorithms for detection. In this investigation, we first describe an efficient algorithm, based on dynamic programming, that can be used in real-time for tracking the ground. We then demonstrate its accuracy through a quantitative comparison with other proposed ground-tracking methods, and a qualitative comparison showing that its ground-tracking is consistent with human observations in challenging terrain.





Comparison of algorithms for finding the air-ground interface in ground penetrating radar signals

In using GPR images for landmine detection it is often useful to identify the air-ground interface in the GPR signal for alignment purposes. A number of algorithms have been proposed to solve the air-ground interface detection problem, including some which use only A-scan data, and others which track the ground in B-scans or C-scans. Here we develop a framework for comparing these algorithms relative to one another and we examine the results. The evaluations are performed on data that have been categorized in terms of features that make the air-ground interface difficult to find or track. The data also have associated human selected ground locations, from multiple evaluators, that can be used for determining correctness. A distribution is placed over each of the human selected ground locations, with the sum of these distributions at the algorithm selected location used as a measure of its correctness. Algorithms are also evaluated in terms of how they affect the false alarm and true positive rates of mine detection algorithms that use ground aligned data.

Table 2. Results of comparisons of algorithm ground estimates human opinions, sorted by best average.

Algorithm	Average x100	Best x100	# Best = 0	Time (sec/scan)
Dynamax+	95	98	286	0.071
Viterbi Ground Max	94	98	389	0.024
Viterbi Ground SVDD	94	97	457	0.114
SVDD-Ground	93	95	828	0.086
X1	92	94	899	0.002
Snakes	89	92	1354	0.790
Polyfit SVDD Snapped	85	88	1906	0.062
Polyfit Max Snapped	85	88	1970	0.003
FastSnakes	84	86	2243	0.296
Global Max	81	83	2847	1.6×10^{-4}
Polyfit Max	73	76	2264	0.003
Polyfit SVDD	73	75	2263	0.062

Random set framework for multiple instance learning

Multiple instance learning (MIL) is a technique used for learning a target concept in the presence of noise or in a condition of uncertainty. While standard learning techniques pres- ent the learner with individual samples, MIL alternatively presents the learner with sets of samples. Although sets are the primary elements used for analysis in MIL, research in this area has focused on using standard analysis techniques. In the following, a random set framework for multiple instance learning (RSF-MIL) is proposed that can directly perform analysis on sets. The proposed method uses random sets and fuzzy measures to model the MIL problem, thus providing a more natural mathematical framework, a more general MIL solution, and a more versatile learning tool. Comparative experimental results using RSF-MIL are presented for benchmark data sets. RSF-MIL is further compared to the state-of-the-art in landmine detection using ground penetrating radar data.

Table 2
AUC for RSF-MIL on benchmark datasets.

Algorithm	Musk 1	Musk 2
RSF-MIL	0.948	0.953
MIRVM	0.942	0.987
MIBoost	0.899	0.964
MILR	0.846	0.795
MISVM	0.899	-

Support vector data description for detecting the air-ground interface in ground penetrating radar signals

In using GPR images for landmine detection it is often useful to identify the air-ground interface in the GRP signal for alignment purposes. A common simple technique for doing this is to assume that the highest return in an A-scan is from the reflection due to the ground and to use that as the location of the interface. However there are many situations, such as the presence of nose clutter or shallow sub-surface objects, that can cause the global maximum estimate to be incorrect. A Support Vector Data Description (SVDD) is a one-class classifier related to the SVM which encloses the class in a hyper-sphere as opposed to using a hyper-plane as a decision boundary. We apply SVDD to the problem of detection of the air-ground interface by treating each sample in an A-scan, with some number of leading and trailing samples, as a feature vector. Training is done using a set of feature vectors based on known interfaces and detection is done by creating feature vectors from each of the samples in an A-scan, applying the trained SVDD to them and selecting the one with the least distance from the center of the hyper-sphere. We compare this approach with the global maximum approach, examining both the performance on human truthed data and how each method affects false alarm and true positive rates when used as the alignment method in mine detection algorithms.

Table 1. Results of evaluation of ground detection algorithms with respect to truthed ground for data sets A and B with varying number of estimates from 1 to 5.

n	Algorithm	RMSE		Max error		Frames /w Error > 5		Scans /w Error > 5	
		A	B	A	B	A	B	A	B
1	Global Max	8.93	48.24	250	408	169	704	339	7300
	SVDD Ground	6.86	6.05	248	350	25	95	74	190
2	Global Max	4.57	7.79	244	351	142	152	202	253
	SVDD Ground	2.85	0.63	223	27	5	33	11	59
3	Global Max	3.19	3.39	199	129	133	111	170	137
	SVDD Ground	1.55	0.41	223	27	1	22	2	32
4	Global Max	2.26	2.79	122	129	130	98	162	119
	SVDD Ground	0.04	0.38	3	27	0	19	0	27
5	Global Max	2.18	2.49	92	117	130	98	162	116
	SVDD Ground	0.03	0.32	2	27	0	15	0	21

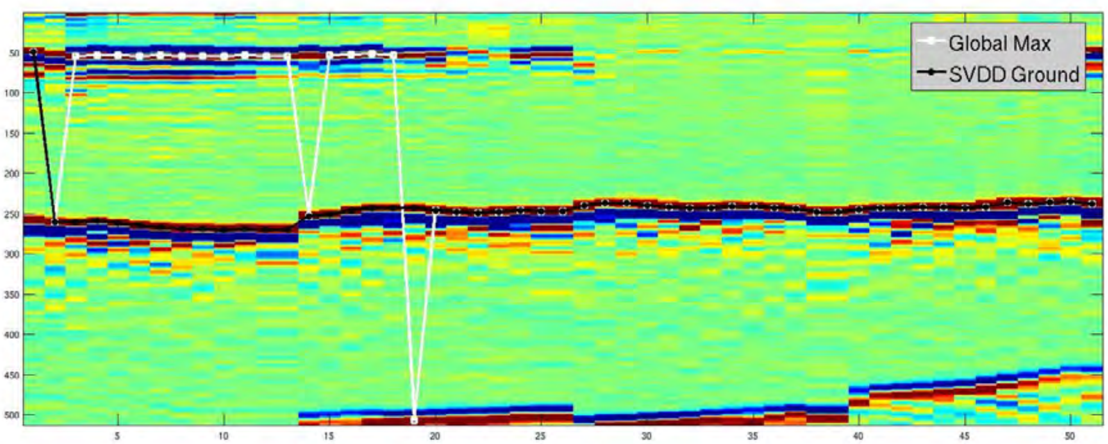


Figure 4. SVDD Ground and Global Max estimates in a frame for data set A.

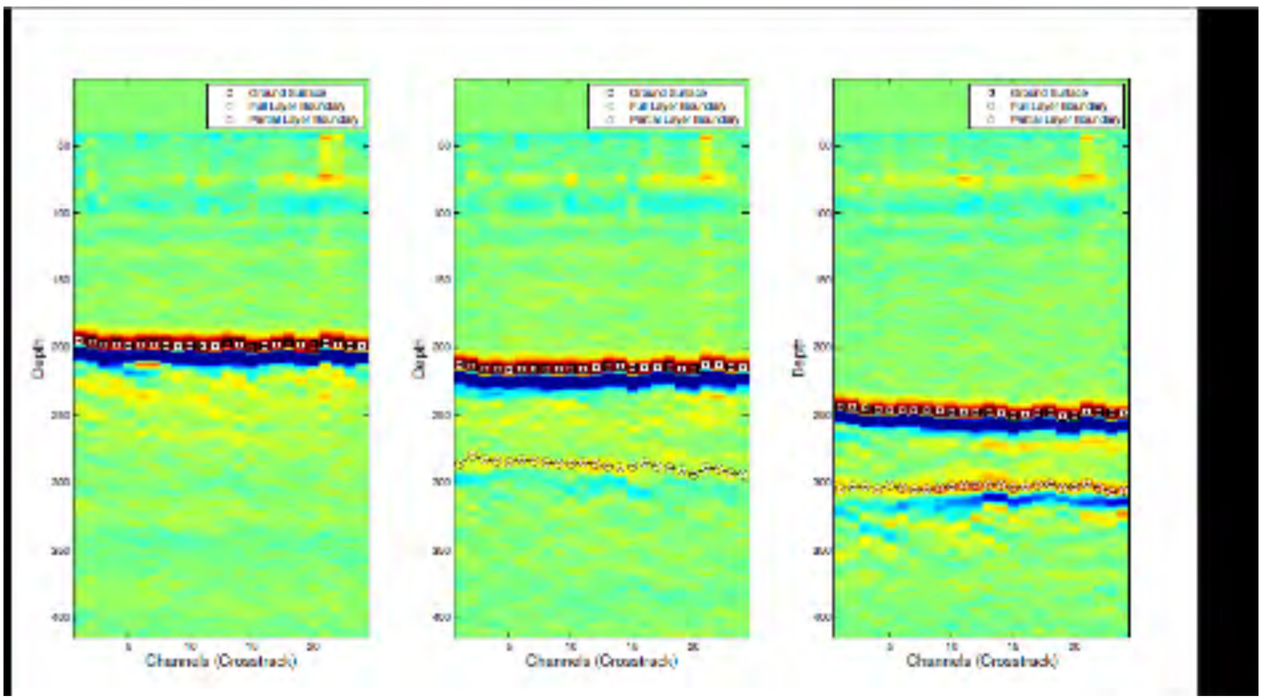
2011-2012

An efficient multiple layer boundary detection in ground-penetrating radar data using an extended Viterbi Algorithm

In landmine detection using vehicle-mounted ground-penetrating radar (GPR) systems, ground tracking has proven to be an effective pre-processing step. Identifying the ground can aid in the correction of distortions in downtrack radar data, which can result in the reduction of false alarms due to ground anomalies. However, the air-ground interface is not the only layer boundary detectable by GPR systems. Multiple layers can exist within the ground, and these layers are of particular importance because they give rise to anomalous signatures below the ground surface, where target signatures will typically reside.

In our research, an efficient method was developed for performing multiple ground layer-identification in GPR data. The method is an extension of the dynamic programming-based Viterbi algorithm, finding not only the globally optimal path, which can be associated with the ground surface, but also locally optimal paths that can be associated with distinct layer boundaries within the ground. In contrast with the Viterbi algorithm, this extended method is uniquely suited to detecting not only multiple layers that span the entire antenna array, but also layers that span only a subset of the channels of the array. Furthermore, it is able to accomplish this while retaining the efficient nature of the original Viterbi scheme.

A sample of layer tracking results are shown below.

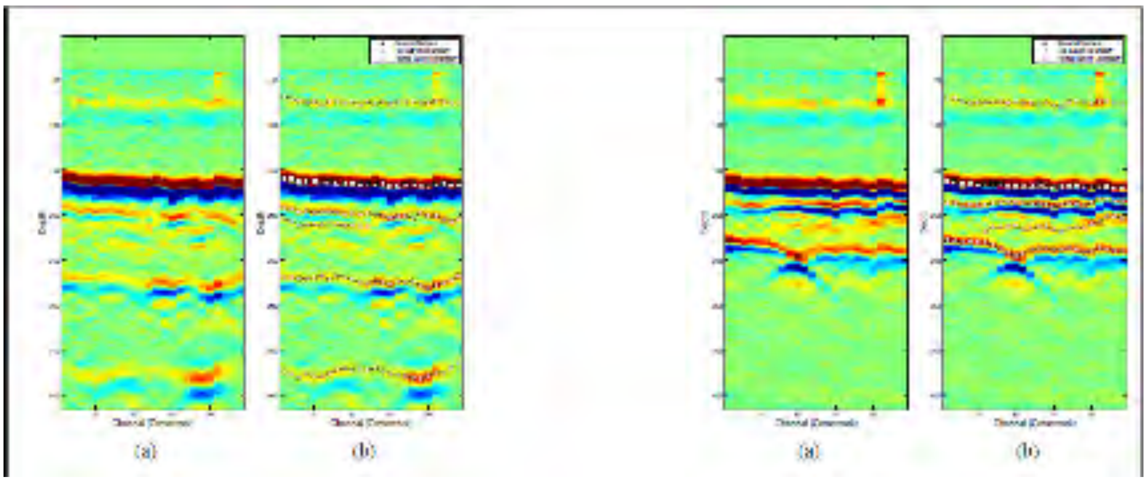


Our method was shown to accurately detect layer boundaries using an extended Viterbi method called reciprocal pointer chains while retaining the complexity of the original Viterbi algorithm. This is important because the typical application scenario we anticipate is use by a vehicle-mounted system performing landmine detection in real-time.

Reciprocal pointer chains for identifying layer boundaries in ground penetrating radar data

Identifying the ground surface in ground-penetrating radar (GPR) data is useful and can be done efficiently and accurately using the Viterbi algorithm. This involves representing the radar image as a trellis graph and solving for the optimal path. To identify multiple layer boundaries in a radar image in this manner, it is necessary to find multiple disjoint paths through the trellis. Two main types of algorithms currently exist that find the k best disjoint paths whose aggregate sum is minimized. However, this criterion has drawbacks. Instead, we have researched and developed a novel criterion for choosing multiple disjoint paths in a trellis that we call the reciprocal pointer chain. This criterion has both a nice intuitive and theoretical justification, and leads to an algorithm with better qualitative results and significantly lower computational complexity than any of the methods previously proposed.

Sample results are shown below.



Our developed algorithm computes RPCs in the trellis representation of the GPR image and declares a subset of these to be layer boundaries. First, the left and right backpointers are computed using the Viterbi algorithm, which is run twice and is O(CN2). Next, all of the RPCs in the trellis are computed from the backpointers. This is straightforward and can be done with an algorithm similar to a depth-first search. This stage of the algorithm is O(CN). From there, only those RPCs that are longer than some minimum length and more probable than some threshold are kept. In this way, the algorithm determines the number of layer boundaries automatically. We can avoid explicitly including a dependence on the number of RPCs in the computational complexity because we can bound the number of possible RPCs to be < CN. Therefore, the complexity of the combined algorithm in the worst case is O(CN2), which is the same as the original Viterbi algorithm.

2012-2013

Optimal Fusion of Alarm Sets from Multiple Detectors Using Dynamic Programming

Automated target detection is a vast field encompassing many technologies and methodologies. In a typical approach, data from a sensor is organized into discrete points of interest, or alarms, where the potential presence of a target is evaluated. A detector produces a confidence score indicating the relative likelihood that an observation at a point corresponds to a target. A confidence-based algorithm serves as a binary classifier that labels data as either target or non-target by setting an operating or decision threshold, t. In other words, all points with confidence $c > t$ are considered targets, and all points with $c < t$ are considered non targets. In this discussion, we refer to a sensor-algorithm pair as a detector, and a discrete observation or point of interest as an alarm.

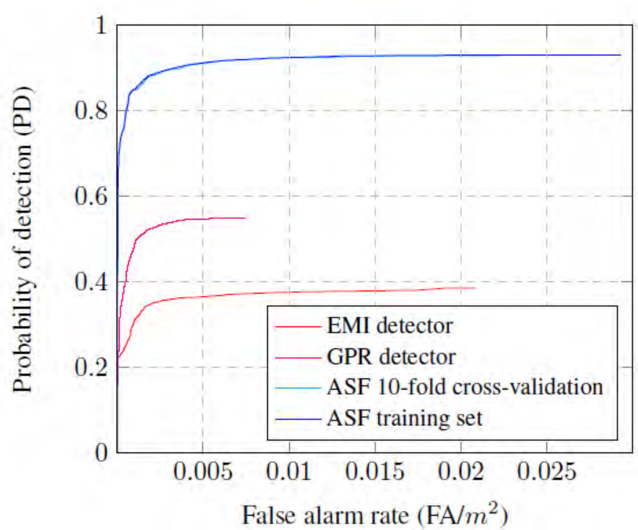
The performance of a detection algorithm in the field depends on its chosen operating threshold and can be evaluated in a number of ways. One way to evaluate it is by simple classifier accuracy—the percentage of accurately classified targets and non-targets. However, this measure fails to take into account imbalanced class distributions and the different costs associated with missed detections and false positives. Imbalanced class distributions can be particularly troublesome in target detection, where non-target observations tend to greatly outnumber target observations. A better performance evaluation tool is the receiver operating characteristic (ROC) curve. A ROC curve can illustrate the performance of an algorithm for all possible operating thresholds simultaneously.

Fusion methods can help with both performance assessment and optimization. However, typical fusion methods require that multiple detectors operate on the same points of interest. This allows complementary information from multiple detectors to aid the binary decision on the presence or absence of a target at a given point. A problem occurs when multiple sensors produce alarms asynchronously so that points of interest from different sensors do not coincide. In this case, typical fusion methods are not applicable.

Our research seeks to address the problem of joint performance assessment and optimization of multiple detectors when the sets of alarms given to or produced by each detector are disjoint or independent. To produce a ROC curve characterizing the joint performance of a set of alarms, a total ordering must be imposed on the elements of the set. The act of putting the alarms in order is a type of fusion we refer to as alarm set fusion (ASF). ASF differs from typical fusion methods in that instead of leveraging complementary information from multiple detectors to improve binary target decisions on individual points of interest, the properties of entire sets of alarms are leveraged to put the combined set of alarms into some optimal order. For example, a detector that tends to produce many true alarms with few false alarms should have its alarms precede those of a detector that produces more false alarms than true, as this will produce a better joint ROC curve. This ordering problem can also be thought of as the problem of mapping the relative confidence output of each detector to some absolute scale. In either case, the relative order of alarms within a single detector are meaningful and should be maintained, thus only monotonic mappings are permissible.

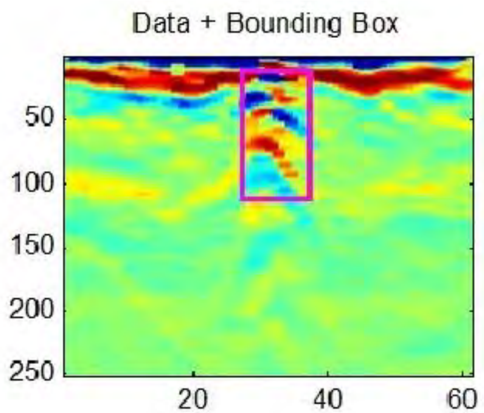
We propose a method using dynamic programming to determine the best ordering of alarms between multiple detectors while maintaining the order of alarms within a single detector (Smock et al.). The ordering of alarms produced during training yields a ROC curve having the greatest area under-the-curve (AUC) achievable with any monotonic mapping or ordering. Additionally, this training method yields a monotonic function that can be used to map alarms from the different detectors into an absolute range so that they can be meaningfully compared.

Initial results on GPR and EMI data show the efficacy of this method when applied using 10 fold crossvalidation. ROC curves for a GPR-based detector, an EMI-based detector, and their fusion using the specific ASF method below. The proposed fusion method demonstrates that the two detectors produce complementary information and a significant improvement over the performance
of the individual detectors is achieved. The un-normalized false alarm rate (FAR) is shown to illustrate a real-valued cost associated with false positives, which must be considered when choosing an operating threshold.



Improvements on Multiple Instance Learning Hidden Markov Model for landmine detection in ground penetrating radar data

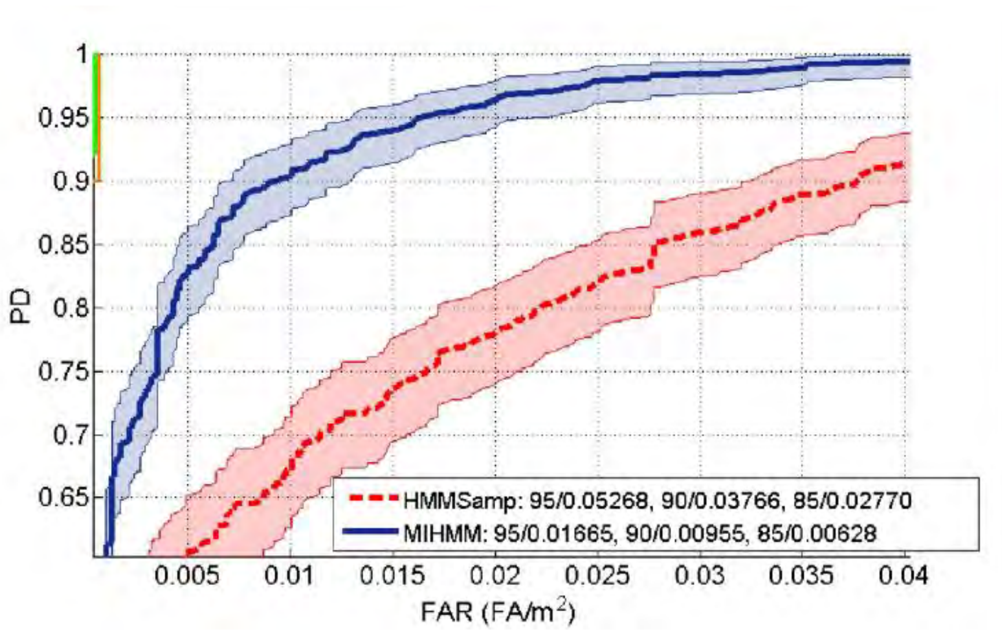
In ground penetrating radar (GPR) images, uncertainty is present. For example, there are areas (subimages or feature sets) in an image that contain a target and areas that do not. However, ground truth is provided only per image and not for the subimages. Therefore this learning scenario provides one class label for multiple instances.



The multiple instance learning (MIL) model has also successfully been used in landmine detection to eliminate the problems associated with the bounding box approach, and has shown considerable success. Previously, hidden Markov model (HMM) based algorithms that utilize time series data are known to be very useful in landmine detection. Previously, we developed MI-HMM which learns an HMM using MIL and in the following we extend this discussion and present experimental results.

In our research we test using a real-world landmine dataset (Bolton et al.). In GPR images, scanning from left to right, a landmine signature would appear as a rising edge followed by a falling edge. Therefore, edge features are computed from GPR images and edge feature sequences are constructed for each horizontal image scan. The goal is to learn the horizontal patterns indicative of a landmine signature using an HMM model. In our experiments, the MI-HMM is compared to a state-of-the-art HMM; a benchmark approach that is currently used in the field, which is referred to hereafter as the "standard HMM".

ROC results for the both the standard HMM and the MI-HMM without sequence trimming.



ROC results for the both the standard HMM and the MI-HMM using the sequence trimming are shown below. The ROC result of the sequence trimmer only is also presented and called "Prescreener" (not to be confused with the prescreening algorithm).